

Motherhood and Income Inequality: A Cross-Country Analysis

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Abstract

This paper attempts to analyze the gender wage gap in the United States and other economically developed nations. Despite a significant convergence of the income gap between men and women in the US, recent years have seen a lag in this convergence. This paper aims to specifically see the costs of motherhood on the occupational decisions of women, their career path, and the earning penalties as a result of children. I analyze government-mandated paid maternity leave and new parent protection rights and their impact on income inequality as well as their potential to lessen the gap.

I. Introduction

The approach of many researchers in recent years on analyzing gender income inequality has changed dramatically. This is because factors that have historically influenced income inequality have drastically evolved. These changes can be directly seen in history. In the US, an important catalyst to recognize would be the effect WW2 had on female workforce participation. Post-World War II saw an increase in two-income households and ultimately changed employment and the job industry forever. Additionally, in the US the difference in education levels between men and women has disappeared almost entirely. Many studies have concluded education levels along with a few other factors contributed to the convergence of the wage gap previously. The question remains then, what factors can be associated with the current gender income inequality in the United States and across OECD Countries?

The focus has now shifted to the penalty of children imposed on women and its effects on their career paths and annual salary. Historically, the responsibility of child care has lain on the shoulders of women. In the past century, two-income households in the US have become normal. Despite this, the responsibility of children typically is still placed on women. Moreover the burden of this “child penalty” is still visible and seen directly through gender income inequality.

Thus in order to see the impact of the child penalty in the United States and what can be done to change it, this study will conduct a cross-country analysis to determine the association between a country’s accommodation policies for working women with children and income inequality. I analyze a set of OECD countries with varying policies on mandatory paid/unpaid maternity leaves. The US is the only country in the OECD without a government-mandated maternity leave (OECD Family Database). On the other hand countries like Bulgaria have upwards of 58.6 weeks of paid maternity leave mandated (OECD Parental Leave Systems). Moreover, the United States despite having a robustly developed economy has a rather high Gini Coefficient of 41.1 compared to other nations. These dramatically different numbers and inconsistencies relating to paid maternity leave and the Gini Coefficient led me to my hypothesis.

Higher government-mandated maternity leave periods will lead to lower Gini Coefficients in respective countries. Therefore, the more accommodating a country’s government is to new mothers and their careers, the less mothers will be affected by the child penalty, and thus the gender income inequality will be lower in that country. I chose my primary independent variable after lots of research regarding the “career costs of children” on new mothers and the “child penalty”. Consistent research has shown that in

modern-day periods in economically developed nations, much of the remaining gender wage gap manifests itself not necessarily in all women, but particularly in women with children and women planning to have children. Analyzing government policy that protects new mothers, is a simple, measurable way to further test these findings.

II. Literature Review

Kleven, Landais, and Søgaaard (2018) conducted a longitudinal study in Denmark that analyzed gender income inequality over time and the cost of children for women and their careers. Now that education levels between men and women have converged almost entirely, this study analyzes the particular effect of children on the careers of women. Separating the career paths and incomes of women with children and women without children gave the researchers a more clear picture of the gender wage gap and opened up new thoughts on what factors could allow the wage gap to converge in the future. This study defined the three factors that earning penalties manifest from. These sources of earning penalties are labor force participation, hours of work, and the wage rate. They found that holding other factors as equally as possible, children create a gender gap in earnings of around 20% in the long run according to Kleven, Landais, and Søgaaard (2018). Additionally, this paper actually concluded that despite an overall convergence of gender income inequality, career child penalties have increased in recent decades. They increased by 40% from 1980 to 2013- from 40% to 80%. The researchers used a dynamic decomposition framework for their study in Denmark from 1980-2013. They attempted to dive into not only gender inequalities in earnings but other factors contributing to gender inequality in the workforce. One example of this would be the occupational decisions of women even before becoming a mother to better accommodate for caring for a child in the future. This creates a domino effect because it creates cultural occupational norms with male-dominated and female-dominated industries. Women then feel pressure to enter into more traditional female roles and more pressure to turn away from male-dominated industries that potentially have higher earning trajectories. Ultimately, this environment where women must choose between family and career affects the woman's career choices and thus their income. This is one of the "dynamic effects" this study found that could be hindering the convergence of income inequality between men and women. The research implies that the unexplained income gap is can now be attributed to "child penalties" rather than solely labeling the gap as due to discrimination.

Adda, Dustmann, and Stevens (2016) explain how children factor into gender income inequality. The researchers used analysis to show how women with children and women planning on having children

experience a loss in earnings opportunities, loss in skill associated with children, as well as make alternative occupational decisions by choosing more child-friendly opportunities. It also looks at the long-run effects of policies that encourage fertility. They found that there are considerably smaller short-run effects caused by the child penalty. Although the researchers still found that despite significant improvements over the last few decades, the wages of women are consistently lower than that of men (see Blau and Kahn (1996), and Weichselbaumer and WinterEbmer (2005) for evidence) are often underrepresented in leading positions, and their careers develop at a slower pace. Adda, Dustmann, and Stevens (2016) concluded that because having children affect a woman's career decisions, women tend to forgo long-term career paths that would give them higher lifetime earnings and career trajectories.

In other literature, Waldfogel (1998) attempted to further decipher the reasoning behind gender income inequality and the "family gap" in pay for women with children. Waldfogel (1998) actually analyzed societal trends and norms in the United States and how they were different in other OECD countries with lower Gini Coefficients. The institutional structure of the US during the decades where the most accelerated convergence occurred was when there was an emphasis on equal pay and equal opportunity policies. Though, while there may have been overarching equal pay policy changes, there was a lack of family policies, like maternity leave and child care infrastructure, that supported mothers and families. Industrialized countries where family policy was supported actually were successful in narrowing the family gap. Waldfogel (1998) concluded that because of the lack of government accommodation, the family gap is larger in the US, and thus may be one of the reasons why the Gini Coefficient is larger in the US compared to other industrialized countries. Waldfogel (1998) then listed her three potential causes of the family gap. The first hypothesis discussed the motivation of mothers and that they are simply less likely to enter the workforce and develop a career because they prioritize their children. The second potential cause could be that employers discriminate against mothers. Essentially, employers are less inclined to invest in women of child bearing age because they suspect that mothers will not prioritize their career. Lastly, Waldfogel (1998) discusses the structural barriers to mothers in the job market. Without job-protected maternity leave, in a society where company specific experience, tenure, and a mutually beneficial relationship between employer and employee is valued, the family gap will remain.

In recent literature regarding income inequality I have read, none have directly compared government policy regarding new parenthood to income inequality and ran statistical tests to understand it. There has been significant research on the impact of children on income inequality, but there is still so much more to learn. I attempt to dive deeper into the measurable policy factors regarding motherhood to

see if the child penalty can be further confirmed and even combatted through simple changes in government legislation. The nature of this paper makes it imperative to use a unique cross-country analysis. Lastly, the outcome and findings of this paper have the potential to find solutions that can be implemented to converge gender wage gaps across the world.

III. Data

This study is a cross-country analysis of gender income inequality and motherhood. The sample size consists of 35 OECD countries. Although this sample size is small, it was necessary given the nature of this study. First, finding consistent accurate data to analyze gender income inequality, particularly regarding mothers, provides many difficulties. But more importantly, there are many different causes and factors that influence income inequality around the world as seen in many different econometric studies. The goal of this research is to get a step closer to understanding what is hindering the convergence in the US and economically advanced countries. I attempt to analyze a micro-aspect of gender income inequality in countries with typically more advanced and high-income economies. Additionally these countries have more similar gaps in education between men and women. To help combat a small sample size and not lose too many observations, I only included the most important independent control variables.

These countries were chosen because they have the most consistent data from a reliable source. The independent variable is the number of weeks of maternity leave mandated by the government in each country. This study aims to analyze a micro aspect of gender income inequality, but more specifically the cost of children on mothers and their careers and wages. I have read and learned from various studies that in recent decades, the likely cause of the gender wage gap can be more accurately attributed to children and motherhood. Thus to see this gap converge, steps need to be taken to allow workforces to be more accommodating. The most rapid way this can be achieved is by governments imploring their employers to give rights to working parents. One very visible indication of whether or not governments are accommodating and aware of this issue is through the government-mandated paid maternity leave and paternity leave. In this study, I aim to focus on maternity leave as the primary independent variable.

Table 1: Variable Descriptions

Variable	Description	Year	Units	Source
gini	GINI Coefficient for income inequality	2021	Index (0, 1)	OECD
mLeave	weeks of government-mandatory paid maternity leave	2018	weeks	OECD
gdppc	GDP per capita	2019/2020	USD/person	OECD
gpiedu	Gender Parity Index- ratio calculated from percent of men to women who attained at least upper secondary education	2019/2020	Index (0, 1)	OECD

Table 2: Descriptive Statistics

Variable	Observation	Mean	Std. Deviation	Min	Max
gini	34	32.31	4.50	24.20	41.9
mLeave	34	19.68	10.14	0	52
gdppc	34	55549.02	36364.28	19127.38	224989.4
gpiedu	34	1.02	0.06	0.82	1.21

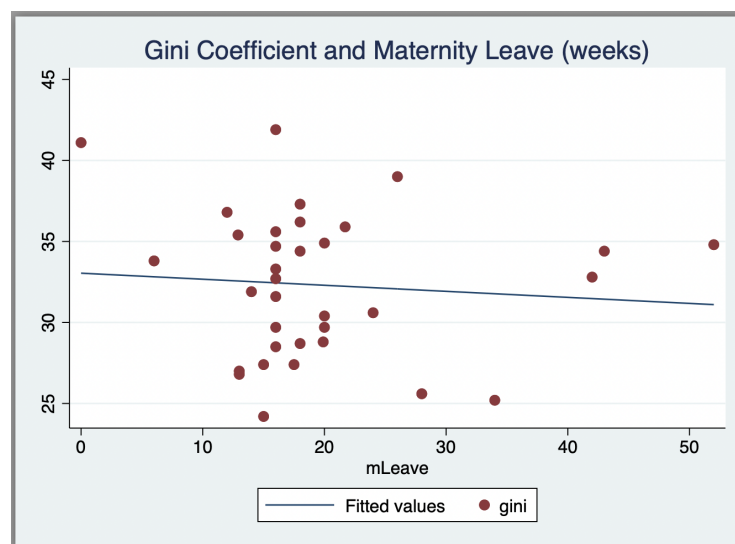
The first and most obvious factor that must be considered when measuring income inequality would be economic development (Kaasa 2005). Most economists model the relationship after Kuznets' research that as GDP grows, inequality will experience an initial increase and then decrease, resulting in an inverted U relationship (Kuznets' 1955). One proposition discusses the ease of upward mobility for entrepreneurs in wealthier nations (Chang and Ram 2000). There have also been a few studies that conflict with Kuznets' general hypothesis (Gustafsson and Johansson 1997). Regardless, there has been enough discussion over economic development relating to income inequality that GDP per Capita will be the first independent control variable of this study.

The second factor to consider would be demographics. The most notable demographic factor that has evidence of affecting income inequality would be education equality and levels between men and women. Like GDP and income inequality, there have been many studies discussing education levels and their effect on income disparities with conflicting results. In theory, if women have equal access to education as men, then they are more likely to enter the workforce with jobs at the same level as men. Thus, lower education inequality should be associated with lower income inequality. Many studies

support this association (Kaasa 2005). Although, one particular study analyzing education levels in the US and income found that countries with more schools nationally experienced higher levels of income inequality (Sylvester 2002).

There are a few different aspects of maternity leave that are important for this study. The first is how many weeks do governments mandate employers to give new mothers maternity leave. The second is the amount of pay these mothers receive during maternity leave. Each government has its own unique plan. These range from tiered maternity leave systems where as the weeks from childbirth increase, the less proportion of pay a mother gets to zero weeks of paid maternity leave as mandated by the US government. This study specifically analyzes weeks of maternity leave mandated by each government with the assumption that the greater the weeks given to the mother, the more accommodating the country is. The data on maternity was pulled from OECD Statistics represents data from 2018. The three-year buffer period allows for all the data to be accurate and collected from more countries, while also maintaining the relevance and application of using the data to make modern-day analysis.

The dependent variable used to measure income inequality in each OECD country is the Gini Coefficient for income inequality. The Gini Coefficient is a widely accepted index that measures inequality. The Gini Coefficient was pulled from all 35 countries and used in the regression analysis. The coefficient ranges from zero to one-hundred. A score of zero indicates zero inequality whereas a one-hundred indicates perfect inequality. In other words, the higher the score the more income inequality can be seen in the distribution of the population in a country. The Gini coefficient can also be defined as the difference between the Lorenz curve and the line of perfect income equality.



The scatter plot above represents the correlation between the gini coefficient and maternity leave. It indicates that there is not a clear relation between gender income inequality and maternity leave. For my hypothesis, this is discouraging to see, although there is much to learn from this scatter plot. The United States is the only OECD country that does not mandate any sort of paid maternity leave. Additionally, the United States has one of the highest Gini Coefficients, one of only 2 countries in the 40s. This is quite interesting because income inequality and gender income inequality has been shown to be lower in countries with developed economies. The United States has among the highest GD

Before performing regression analysis on the data collected, a few checks must be made. The Gauss Markov Assumptions are used to ensure the data is as viable and unbiased as possible. The first check is for linearity. The parameters we are estimating are linear given our linear regression equations:

$$y = B_0 + B_1X_1 + B_2X_2 + \dots B_kX_k + u$$

The second check is for randomness. All data used in this study was gathered from credible sources (OECD Database and World Population Review). These sources used random sampling from populations across the world. The third check is for non-collinearity. The regressors, as seen in the scatter plot above are not perfectly correlated with each other. The gini index and maternity leave have a correlation coefficient of -0.0859 indicating a low correlation.

The fourth assumption is for exogeneity, meaning the expected value of the error term, u , is zero. Income inequality has been studied by many researchers and there are a multitude of factors that could affect income inequality and the Gini coefficient. Therefore this study incorporates independent control variables and multiple regression to ensure the error term, u , is as close to zero as possible. Lastly, the fifth assumption is for homoscedasticity. Because there are variables and factors that influence the Gini Coefficient that is not explicitly stated, the assumption that the error of the variance is constant is unobtainable. Although the regression incorporates independent control variables to help minimize this effect and get as close to constant as possible. Because this assumption is not completely satisfied, conclusions made from the result of this research must account for this and acknowledge that is not the absolute best linear unbiased estimate, but as close to it as possible.

IV. Results

(1) Simple Regression Equation:

$$\text{gini} = 33.06628 - 0.0379502(\text{mLeave}) + u$$

$$(.0765774)$$

(2) Multiple Regression Equation:

$$\text{gini} = 37.68746 - 0.0394048(\text{mLeave}) + .000195(\text{gdppc}) - 5.599675(\text{gpiedu}) + u$$

$$(.079456) \quad (.0000221) \quad (12.60026)$$

OLS Results. Dependent Variable: GINI Coefficient

Independent Variables	(1) SLR	(2) MLR
mLeave	0.038 (.077)	-.039 (0.079)
gdppc	-	.000195 (.0000221)
gpiedu	-	-5.599 (12.600)

Note: quantities in parentheses are standard errors

As shown in the linear regression equation, there is a negative linear relationship between the Gini Coefficient and weeks of mandated maternity leave. This aligns with the hypothesis that as paid maternity weeks increase, the income inequality between men and women decreases. In the multiple regression analysis, a secondary and tertiary independent variable are both introduced. This is to help with the ceteris paribus effect.

After analyzing the regressions, the data is not significant enough to support my initial hypothesis. The coefficient of determination was far too low meaning based on the data collected, there is little to no correlation between the Gini Coefficient and mandated maternity leave. Based on my analysis, one additional week of mandated maternity leave results in a 0.039 point decrease in the Gini Index of that country.

At the 95% confidence level the t-value associated with my degrees of freedom is 1.697 for a one tailed test. My null hypothesis would be that maternity has a negative effect on the gini coefficient and thus an increase in mandated maternity leave (by weeks) would lower the gini coefficient. In other words, mandating maternity leave will lower gender income inequality. Because my t-value for maternity leave (-0.5) is less than 1.697, it is not in the rejection zone. Therefore it fails to reject the null hypothesis.

A very important aspect of this study is looking at the relationship between GDP per capita and the Gini coefficient. Previous literature has shown, especially in Kuznets' (1955) study, that these variables show a U relationship. If Maternity leave is linear with GDP per capita, but GDP per capita is U shaped and non-linear with Gini, then maternity leave and the Gini Coefficient may have a relationship given these variables but that relationship just may not be linear. Further tests and data manipulation including potential dropping outliers and other strategies which may be beyond the scope of this class, would need to be done to prove this possibility.

V. Extensions

Today, the COVID-19 Pandemic has drastically changed the job market and also the culture around the workplace. Many companies were forced to adjust to a completely virtual workplace at the start of the pandemic. Since then, employers have developed new strategies and a more robust system to efficiently work virtually. Many employers have succeeded in this transition and are developing long-term hybrid and virtual workplaces. The concept of working a 9am to 5pm job and having rigid structure for your employees is now considered outdated and malleable. This inherently creates more flexibility for new mothers and families. It will be interesting to see once data is collected from the next few years, the impact the Pandemic has had on the child penalty. In future studies, I would like to analyze how new mothers take maternity leave, if they need to all (given they are allowed to work virtually from home), and whether or not this can close the family gap further. Will the pandemic and a new virtual/hybrid world help converge the gender income inequality gap?

Another point of interest would be to consider parental leave and family leave. Within recent years a multitude of countries and employers around the world have implemented new policies that give new fathers and parents as a whole job-protected paid and unpaid leave. Giving fathers the option to also take leave could change the culture around who the responsibility of child-care is defaulted on and also allow parents to share the burden of child care so both can also prioritize their career, gain experience and receive more equal earnings.

In the US, although there is no government-mandated maternity leave, there are some states and some large firms that do provide paid parental leave. As of 2017, according to the NCLS, only 14% of Americans had access to paid family leave. As of 2020, California, New Jersey, Rhode Island, New York, Washington, and Washington D.C are the only state governments that mandate paid family leave. It would be interesting to see how these newer mandates (For example. Washington's new law did not go into

effect until 2020.) affect the family gap in these states. A state level comparison would be interesting to see this effect.

Additionally, because GDP per capita is so large compared to my other data, I ran a regression using the log(GDP per capita) to see if it would better support my hypothesis.

(3) Multiple Regression Equation:

$$\text{gini} = 33.29 - 0.04(\text{mLeave}) + 1.17(\text{gdppc}) - 5.62(\text{gpiedu}) + u$$

(0.08) (4.08) (12.75)

This multiple regression was interesting because it made the gdppc coefficient larger and actually the coefficient of determination was lower. Therefore, because it supported my hypothesis less, I decided to use the original regression.

I used an F-statistics test to test for the multicollinearity between my two independent control variables, GDP per capita and the Gender Parity Index. My null hypothesis would be that the two variables are not jointly significant. I first performed a restricted and unrestricted regression and analyzed their residual sum of squares.

SSR Restricted: 647.22

SSR Unrestricted: 641.96

$$((647.22 - 641.96) / 2) / (641.96 / (31 - 3 - 1)) = 0.127$$

The critical value associated with my degrees of freedom at the 5% confidence interval is 3.305. Thus because 0.127 is far less than 3.305, it falls out of the rejection zone. Therefore the test fails to reject the null hypothesis. This test was difficult because my sample size was quite small. This made falling in the rejection zone quite high because of the small sample size and low amount of variables creating a fairly large critical value. These two variables may potentially show some collinearity but given the research of the key factors that affect income inequality, I deemed these two variables to be the most important control variables and decided to include them in this study.

VI. Conclusion

The concept of the family gap or the child penalty in income inequality still remains to be an incredibly important topic of conversation for economists analyzing income inequality in advanced

economies. More robust tests must be made to further understand the true effect having children has on mothers. The data in this test fails to support my original hypothesis, but the income inequality for mothers still remains. Thus more research needs to occur to discover more factors that could influence the family gap. As this family gap increases and diverges despite the overall convergence of gender income inequality, governments must find ways to combat and assist new parents.

There are many ways governments in these economically developed nations can attempt to assist new parents. It would be interesting to see a study to see whether or not access to affordable, dependable child care, whether private or public, has an effect on the family gap. Governments budgets can also be allocated to subsidizing child care, parental leave, maternal leave, and even paternal leave.

Finally, with the option of a virtual workplace becoming normalized, the concept of paternal leave, or the dire need for it, may even become obsolete. If more flexible job accommodations are implemented, mothers' approach to their career may change. Moreover, employer bias against mothers may also change. The job market is approaching a period of drastic change and restructuring. This change may have the potential to further converge gender income inequality across the US and the world.

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Appendix:

Appendix A: List of Countries

Australia, Austria, Belgium, Canada, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States, Czech Republic

Appendix B:

```
. regress gini mLeave
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Source	SS	df	MS	Number of obs	=	35
Model	4.93173232	1	4.93173232	F(1, 33)	=	0.25
Residual	662.655125	33	20.0804583	Prob > F	=	0.6235
				R-squared	=	0.0074
				Adj R-squared	=	-0.0227
Total	667.586857	34	19.6349076	Root MSE	=	4.4811

gini	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
mLeave	-.0379502	.0765774	-0.50	0.623	-.1937481	.1178478
_cons	33.06628	1.675357	19.74	0.000	29.65775	36.47482

Appendix C:

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. regress gini mLeave gdppc gpiedu
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Source	SS	df	MS	Number of obs	=	34
Model	25.2866343	3	8.42887808	F(3, 30)	=	0.39
Residual	641.960719	30	21.3986906	Prob > F	=	0.7583
				R-squared	=	0.0379
				Adj R-squared	=	-0.0583
Total	667.247353	33	20.2196168	Root MSE	=	4.6259

gini	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
mLeave	-.0394049	.079456	-0.50	0.624	-.2016757	.1228658
gdppc	.0000195	.0000221	0.88	0.387	-.0000258	.0000647
gpiedu	-5.599675	12.60026	-0.44	0.660	-31.33284	20.13349
_cons	37.68746	12.99598	2.90	0.007	11.14613	64.22879

Appendix D:

. regress gini gdppc gpiedu

Source	SS	df	MS	Number of obs	=	34
Model	20.023611	2	10.0118055	F(2, 31)	=	0.48
Residual	647.223742	31	20.8781852	Prob > F	=	0.6236
				R-squared	=	0.0300
				Adj R-squared	=	-0.0326
Total	667.247353	33	20.2196168	Root MSE	=	4.5693

gini	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
gdppc	.0000193	.0000219	0.88	0.385	-.0000253	.0000639
gpiedu	-5.423003	12.4411	-0.44	0.666	-30.79679	19.95078
_cons	36.74235	12.69818	2.89	0.007	10.84423	62.64046

Appendix E:

. summ gini mLeave gdppc gpiedu

Variable	Obs	Mean	Std. dev.	Min	Max
gini	34	32.30882	4.496623	24.2	41.9
mLeave	34	19.67647	10.13993	0	52
gdppc	34	55549.02	36364.28	19127.38	224989.4
gpiedu	34	1.015105	.0639377	.8223235	1.214286

Appendix F:

. correl gini mLeave
(obs=35)

	gini	mLeave
gini	1.0000	
mLeave	-0.0859	1.0000

Appendix G:

```
. regress gini mLeave gdppc gpiedu
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Source	SS	df	MS	Number of obs	=	34
Model	25.2866343	3	8.42887808	F(3, 30)	=	0.39
Residual	641.960719	30	21.3986906	Prob > F	=	0.7583
				R-squared	=	0.0379
				Adj R-squared	=	-0.0583
Total	667.247353	33	20.2196168	Root MSE	=	4.6259

gini	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
mLeave	-.0394049	.079456	-0.50	0.624	-.2016757	.1228658
gdppc	.0000195	.0000221	0.88	0.387	-.0000258	.0000647
gpiedu	-5.599675	12.60026	-0.44	0.660	-31.33284	20.13349
_cons	37.68746	12.99598	2.90	0.007	11.14613	64.22879

Appendix F:

```
. regress gini mLeave loggdppc gpiedu
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Source	SS	df	MS	Number of obs	=	34
Model	10.5595426	3	3.51984752	F(3, 30)	=	0.16
Residual	656.68781	30	21.8895937	Prob > F	=	0.9219
				R-squared	=	0.0158
				Adj R-squared	=	-0.0826
Total	667.247353	33	20.2196168	Root MSE	=	4.6786

gini	Coefficient	Std. err.	t	P> t	[95% conf. interval]	
mLeave	-.0383911	.0803528	-0.48	0.636	-.2024935	.1257112
loggdppc	1.167894	4.082045	0.29	0.777	-7.168753	9.504542
gpiedu	-5.620829	12.75366	-0.44	0.663	-31.66728	20.42563
_cons	33.29109	22.7653	1.46	0.154	-13.20186	79.78405

Appendix G:

Country	gini	mLeave	gdppc	gpiedu
Australia	34.4	18.0	51742.5742	0.99027947
Austria	29.7	16.0	55651.1062	0.92333709
Belgium	27.4	15.0	52062.8063	1.02196382
Canada	33.3	16.0	48090.9865	1.03104213
Denmark	28.7	18.0	60566.2256	1.05408805
Estonia	30.4	20.0	37984.4736	1.07925408
Finland	27.4	17.5	50810.7308	1.06011561
France	31.6	16.0	42855.9446	0.98997494
Germany	31.9	14.0	54315.5463	0.97719498
Greece	34.4	43.0	28369.4039	1.02624309
Hungary	30.6	24.0	33252.5636	0.96412037
Iceland	26.8	13.0	55213.3837	1.04593176
Ireland	32.8	42.0	95512.5861	1.07356608
Israel	39	26.0	95512.5861	1.01499423
Italy	35.9	21.7	41963.8664	1.06867672
Korea	35.4	12.9	43318.8861	0.94266814
Latvia	35.6	16.0	32028.0558	1.09461078
Lithuania	37.3	18.0	39189.3909	1.04851158
Luxembourg	34.9	20.0	118726.497	0.98586118
Mexico	36.8	12.0	19127.3752	0.96984925
Netherlands	28.5	16.0	59334.6968	0.9924338
New Zealand	36.2	18.0	224989.374	1.01629073
Norway	27	13.0	63293.1969	1.01958384
Poland	29.7	20.0	34003.6081	1.00760043
Portugal	33.8	6.0	34003.6081	1.21428571
Slovak Republic	25.2	34.0	32004.1523	0.98054054
Slovenia	24.2	15.0	40073.2638	0.98423423
Spain	34.7	16.0	38341.4344	1.1013986
Sweden	28.8	19.9	54913.6457	1.02679659
Switzerland	32.7	16.0	71705.4292	0.97762864
Turkey	41.9	16.0	28435.4022	0.82232346
United Kingdom	34.8	52.0	45944.4604	1.0178117
United States	41.1	0.0	63285.2323	1.01664817
Czech Republic	25.6	28.0	42044.2384	0.97371188